Climate variability introduces uncertainty into future emissions pathways

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Abstract

Uncertainty in long-term climate outcomes arises not only from physical processes but also from societal responses to climate variability and change. Here we embed a range of temperature anomalies into an empirically-informed, coupled climate–social model to investigate how natural temperature variability shapes global emissions trajectories. Using Monte Carlo ensembles spanning social, political, and technological parameters, we find that anomalous mid-century warmth accelerates the timing of net-zero emissions by several years, while anomalous cooling delays net-zero achievement. The response scales with the magnitude and persistence of variability with stronger and longer-lasting temperature anomalies producing larger shifts in mitigation timing. Across ensembles, high-variability climates are associated with higher emissions pathways and a greater likelihood of failing to reach net zero by 2100. Externally forced cooling events, such as volcanic eruptions, produce sharp impacts, delaying net zero by nearly a decade through temporary declines in public support for climate mitigation. These findings reveal that climate variability can cascade through perception, politics, and technology adoption to alter the pace of global mitigation, highlighting the sensitivity of emissions pathways to short-term climate signals.

1. Introduction

The magnitude of global warming is the dominant determinant of future climate risks such as heat extremes, severe storms, and sea level rise (IPCC AR6 WG2, 2023). Differences in end-of-century warming translate into divergent societal outcomes, ranging from manageable adaptation challenges to unprecedented economic and ecological damages (Burke et al., 2015; IPCC AR6 WG2, 2023). The largest source of uncertainty in long-term climate projections is not from the physical climate system itself, but rather from the future trajectory of anthropogenic greenhouse gas emissions (Hawkins & Sutton, 2009; Lehner et al., 2023). Anticipating these trajectories is profoundly challenging. Emissions are not determined by a single driver, but by the intersection of multiple domains such as economic growth, patterns of energy production and land use, technological change, political institutions, and human behavior (Riahi et al., 2017; Otto et al., 2020). Each of these domains is complex in its own right, but when coupled together they create nonlinear feedbacks, tipping points, and path dependencies that resist simple prediction (Beckage et al., 2018). Understanding these dynamics is essential for anticipating the levels of greenhouse gas emissions that will shape the planet's future climate.

Most long-term emissions scenarios are generated by integrated assessment models, which link economic activity, energy systems, land use, and social behaviors to greenhouse gas emissions (Riahi et al., 2017). These scenarios provide the inputs that Earth system models use to simulate climate outcomes, forming the backbone of assessments by the IPCC and others (IPCC AR6 WG3, 2023; Eyring et al., 2016). Yet this approach typically treats emissions as fixed inputs (Riahi et al., 2017; Moore et al., 2022), neglecting the possibility that the climate itself, through its variability and impacts, feeds back on public opinion and political action (Ricke and Caldeira, 2014; Moore et al., 2022; Ramanathan et al., 2022). In doing so, it leaves unexplored how climate signals might accelerate or delay the societal momentum needed for mitigation.

A growing body of social science evidence suggests that this omission is consequential (Howe et al., 2019; Ricke and Caldeira, 2014). Extreme weather events and short-term climate anomalies can shape public concern and political support for climate action (Egan and Mullin, 2012; Deryugina, 2013). Some studies link heat waves, droughts, or wildfires to heightened concern and increased support for pro-environment candidates (Howe et al., 2019; Hazlett & Mildenberger, 2020). Effects often depend on social context: perceptions are filtered through ideology, prior beliefs, and local political conditions, leading to heterogeneous societal responses (van der Linden, 2015; Hazlett & Mildenberger, 2020). This indicates that climate anomalies can, under certain conditions, open so-called ‘windows of opportunity’ for policy action (Kingdon, 2003).

At the same time, the physical climate system is highly variable. Internally generated fluctuations such as the El Niño–Southern Oscillation, decadal modes of variability, and externally forced events like volcanic eruptions can amplify or mask long-term warming trends (Deser et al., 2012; Driscoll et al., 2012). Such variability not only affects physical impacts but may alter societal perceptions of climate change and collective willingness to cut emissions (Diffenbaugh et al., 2023; Keys et al., 2022). When climate trends appear to pause or reverse, even briefly, they may foster public narratives that climate change has slowed or that policies are succeeding prematurely. For example, the “global warming hiatus” of the early 2000s illustrates this effect: despite continued greenhouse gas accumulation, a temporary slowdown in global surface warming was widely interpreted as evidence that climate change had paused. This interpretation was amplified in media coverage and political discourse, giving traction to arguments that questioned the urgency of mitigation (Lewandowsky et al., 2016; Medhaug et al., 2017).

Recent modeling and empirical works highlight the need to more explicitly integrate socio-climatic feedbacks into our understanding of emissions pathways. Ricke and Caldeira (2014) showed with an illustrative model that climate variability can delay the “time-to-action” for policy adoption by decades, emphasizing the role of stochastic signals. Beckage et al. (2018) demonstrated that behavioral feedbacks can shift end-of-century warming outcomes by several degrees, while Otto et al. (2020) identified social tipping elements that may accelerate mitigation. More recently, Moore et al. (2022) embedded social, political, and technological dynamics into a coupled model, showing how divergent realizations of these feedbacks can produce global futures ranging from 1.8 °C to 3.6 °C warming. Together, these strands of research underscore that societal and climatic processes when filtered through perceptions of variability, attribution, and political context can amplify or dampen climate outcomes via altered emissions pathways of magnitudes comparable to geophysical feedbacks.

Here we build on this body of work to ask how natural climate variability may shape modeled emissions pathways through social and political feedbacks. Specifically, we investigate: whether variability in temperature anomalies influences mitigation trajectories; how the impact depends on the timescale of variability, from annual to decadal; and how a period of externally forced cooling, such as that induced by volcanic activity, might alter motivation to cut emissions.

By embedding a range of temperature variability into a coupled climate–social model, we assess how climate fluctuations can cascade through opinion and policy to affect the long-term path toward net-zero emissions.

2. Methods

2.1 Coupled Climate–Social Model Framework

To investigate the influence of natural climate variability on future emissions pathways, we use the coupled climate–social model developed by Moore et al. (2022), which integrates social, political, technological, and climatic processes into a single dynamical system. The model represents feedbacks among six primary components: cognition, opinion, adoption, policy, emissions, and climate (Figure 1). Greenhouse gas emissions determine the forced climate response, which contributes to global mean temperature change. In parallel, natural climate variability is prescribed as an exogenous, temperature anomaly sequence. These temperature signals feed into individual cognition, which shapes the distribution of public opinion and support for climate policy (Figure 1). Changes in support affect political responsiveness and the pace of technology deployment, which in turn alter emissions trajectories. The pathway linking temperature variability to future emissions is the focus of this study and is highlighted by bold arrows in Figure 1.

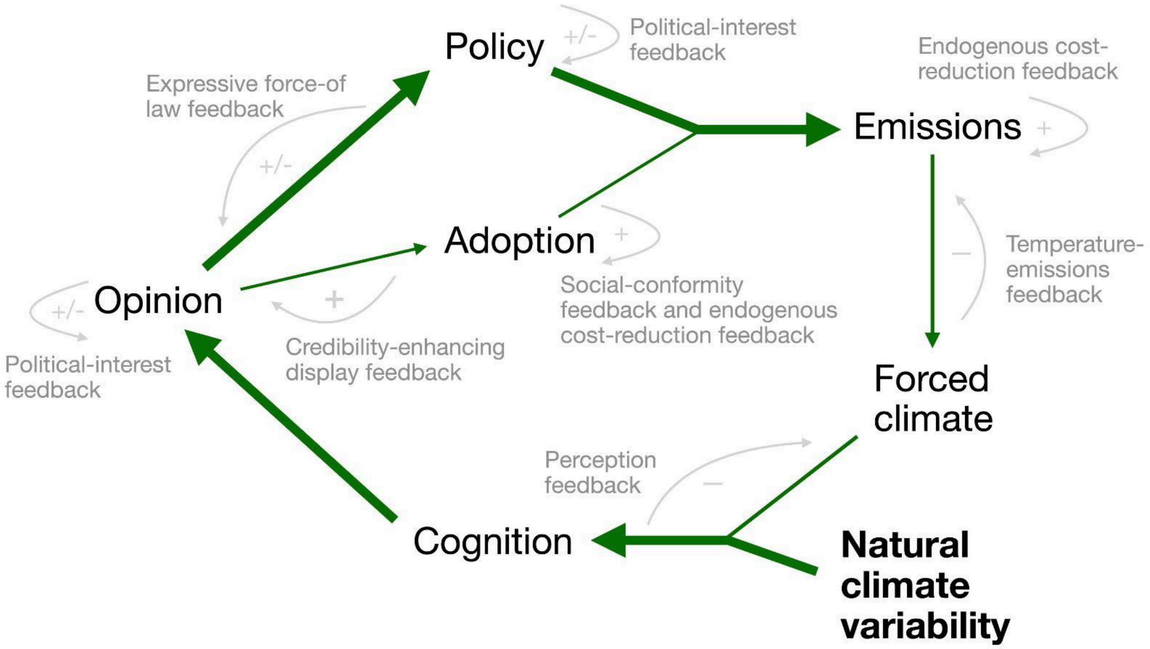

Figure 1: Diagram of the integrated climate–social system, highlighting the pathway from natural climate variability to global annual emissions.

Adapted from Moore et al. (2022). Main modules are shown in black and feedback processes in grey. Bold text and arrows emphasize the pathway examined in this study, linking temperature variability to emissions through cognition, opinion, and policy dynamics.

Interactions among model components occur through temporally lagged feedbacks that introduce inertia and nonlinear dynamics. Changes in perceived climate signals influence opinion only gradually through social persuasion, motivated reasoning, and shifting baselines, meaning that the effect of a temperature anomaly on policy support may unfold over multiple years. Policy responses are further moderated by institutional status quo bias, which requires sufficiently large opinion majorities before policy adjusts and slows the rate at which policy responds before thresholds are crossed. Additional delays arise in the emissions module, where mitigation driven by policy produces persistent but gradually decaying emissions reductions as energy infrastructure and technologies turn over. Together, these lags allow short-lived climate signals to propagate through the system in nonlinear ways, producing delayed or amplified responses across cognition, opinion, policy, and emissions.

Within the cognition component, perceived temperature anomalies are calculated relative to either a fixed historical reference or a shifting baseline defined by a weighted average of the previous eight years of temperatures, capturing the tendency for recent conditions to reset what is considered “normal” (Moore et al., 2019). The cognition module therefore reflects two competing mechanisms: the emergence of a climate-change signal from rising temperatures and the obscuration of that signal by natural temperature variability. It is not known a priori which mechanism dominates, over what timescales, or how persistent its effects may be once downstream policy and technology feedbacks are activated.

Perceived temperature anomalies influence support for climate policy, with asymmetric effects across opinion groups governed by a bias-assimilation parameter. This reflects evidence that individuals tend to place greater weight on information consistent with their prior beliefs, meaning that warm anomalies are overweighted by supporters and underweighted by opponents of climate policy, with the reverse occurring for cool anomalies (Druckman et al., 2019). Acting together, these cognitive filters mean that transient cool excursions can dampen pro-policy support and reinforce the status quo. Through the model’s coupled feedbacks, these shifts in opinion can delay policy adoption and the development of energy-system technologies, potentially producing long-term effects on climate outcomes.

2.2 Monte Carlo Ensemble Design

The Monte Carlo ensemble method provides the basis for our analysis. By sampling parameter values across a range of empirically informed distributions, we generate large sets of plausible futures that span uncertainty in social, political, and technological processes. We conduct several Monte Carlo experiments that differ in how natural variability is generated and prescribed to the model. These experiments are described in the sections that follow and summarized in Supplementary Table S1. In each experiment, runs propagate their prescribed temperature variability through the cognition–opinion–policy loop, yielding annual time series of emissions, temperature, and opinion group distributions. This approach enables us to analyze distributions of outcomes rather than single trajectories without having to rely on the potential shortcomings of any single parameterization.

Parameter ranges follow Moore et al. (2022), where model parameters were informed by published empirical estimates from the psychology, political science, and energy systems literature where available, and further evaluated through hindcasting exercises. In these exercises, Monte Carlo simulations of the opinion and policy modules were compared with observed time series of public opinion and carbon prices across several OECD countries. Parameter combinations that better reproduced these historical patterns were given greater weight, partially constraining the model parameter space.

We introduce one modification to the initialization of public opinion. The original model calibrated the initial share of climate policy supporters to Pew Research Center survey data, yielding a strong pro-policy majority of 71%. Pulling on a range of current global estimates of support for climate policy (Pew Research Center, 2009; UNDP & University of Oxford, 2021; AP-NORC, 2023), we modify the initialization to instead draw the initial supporter fraction from a truncated skew-normal distribution centered on 0.5 (i.e. 50% policy support, see Supplemental

Figure 2). This allows some realizations to begin with pro-policy majorities and others with oppositional majorities.

2.3 Construction of Natural Temperature Variability

We consider three distinct approaches to prescribing natural temperature variability. Across all experiments, variability sequences are pre-generated and exogenous to emissions decisions within each run.

2.3.1 Spectrally Generated Global Variability

In baseline experiments, the default temperature variability scheme is used, where annual global mean temperature anomalies are generated using a stochastic process calibrated to the power spectrum of pre-industrial control simulations output by a fully coupled Earth System Model (Moore et al., 2022). This spectral decomposition is used to reproduce realistic variance across interannual to decadal timescales. These sequences are zero-mean and temporally autocorrelated, ensuring that variability contains realistic persistence without being influenced by transient emissions within the simulation.

2.3.2 Local Variability from CESM Pre-Industrial Control

To represent geographically heterogeneous climate signals from around the world, we replace the stochastic generator with temperature anomaly time series sampled directly from a high-resolution Community Earth System Model pre-industrial control simulation (Hurrell et al., 2013; Chang et al., 2020). We randomly select land grid cells with latitude weighting to approximate equal-area sampling and extract 81-year segments of annual 2-meter temperature anomalies. This procedure imports realistic spatial variability, including differing amplitudes across tropical and midlatitude regions.

2.3.3 Volcanic Variability from CESM Last Millennium

To examine externally forced cooling events, we draw 81-year segments of annual land temperature anomalies from the CESM Last Millennium ensemble (Otto-Bliesner et al., 2016). Segments are selected so that cooling associated with the 1815 Tambora eruption occurs in model year 2030. This experiment allows evaluation of abrupt, short-lived cooling shocks embedded within the coupled social–climate system.

3. Results

We begin with a hypothetical future scenario: what if natural temperature variability in 2025–2034 led to especially warm or cool global conditions? How might these temperature anomalies lead to downstream impacts on support for climate policy and emissions trajectories? This recalls the "climate hiatus" of the early 2000s, which was widely used to question the reality of global warming (Lewandowsky et al., 2016; Medhaug et al., 2017). To test this idea, we average natural variability for each model run in the ensemble over 2025–2034, group runs into temperature deciles, and evaluate associations between the hottest and coldest deciles for the median fraction of the modeled population that supports climate policy (Figure 2a) and the median emissions pathways (Figure 2b). Here, the underlying Monte Carlo ensemble utilizes the default temperature variability scheme, as described in Methods 2.3.1.

Deviations in the fraction of climate policy supporters emerge quickly in the 2020s, with hot temperatures raising support for climate action and cold temperatures reducing it (Figure 2a).

Nearing 2040, the cold and hot deciles converge toward stable pro-policy majorities. Emissions show a similar, albeit delayed behavior, with hotter temperatures leading to an accelerated decline in global emissions. After about 2045, the emissions pathways remain parallel until they eventually reach net zero. The overall impact is a timing shift in the achievement of net-zero emissions by about ±3 years relative to the ensemble median: earlier for "hot-2030s," later for "cold-2030s" (Figure 2b). These outcomes illustrate how temporary temperature excursions can have a long-term, persistent effect on emissions trajectories by influencing path-dependent, coupled feedbacks operating through public opinion, policy, and the energy system.

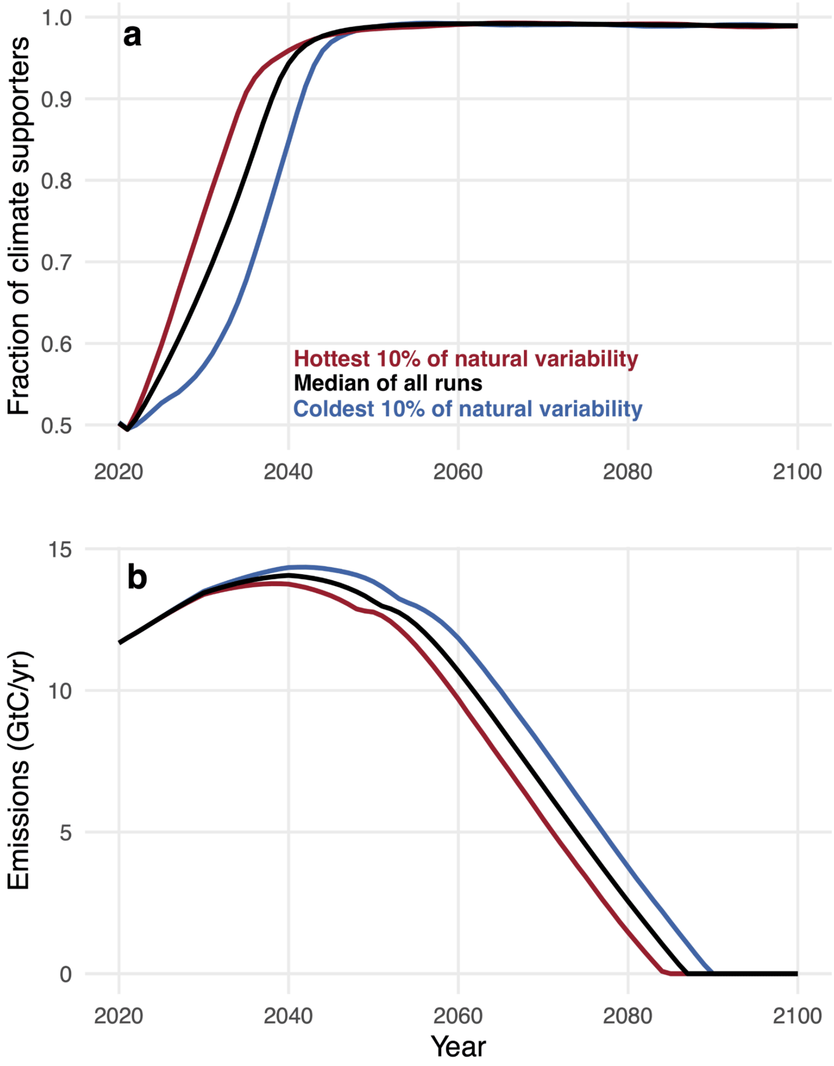

Figure 2: **The coldest and hottest decadal temperature variability influences support for climate mitigation and median emissions pathways.**

Two-panel comparison of median trajectories from the Monte Carlo ensemble: (top) fraction of the population supporting climate policy and (bottom) annual carbon emissions (GtC yr^{-1}). Lines show medians for the coldest 10% (blue) and hottest 10% of runs (red) by average natural temperature variability in 2025–2034 and the median of all runs (black).

To generalize beyond single scenarios, we systematically explore the magnitude and persistence of temperature variability. We bin simulations by the mean temperature anomaly over windows ranging from 1 to 20 years, with each window beginning in 2025. This range of window sizes spans variability timescales from interannual noise to multi-decadal fluctuations. For each bin we calculate the median emissions trajectory and record the year it achieved net-zero. As before, the underlying Monte Carlo ensemble for this analysis utilizes the default temperature variability scheme, as described in Section 2.3.1.

The resulting heatmap (Figure 3) reveals a pattern consistent with Figure 2, that warm anomalies lead to a more rapid achievement of net-zero emissions, while cool anomalies delay. The size of this shift depends on both the duration and magnitude of the temperature anomaly, with stronger and longer-lasting anomalies leading to a greater shift. Cold temperature anomalies exert a somewhat stronger influence on emissions trajectories, with some anomalies nudging the net-zero achievement year by up to two more years than hot anomalies of similar duration and magnitude. This asymmetry partly reflects model mechanics, where support for climate policy tends to rise over time due to a warming climate, leaving limited headroom for additional acceleration during warm periods, while cooling can still erode support and slow policy.

Most bins differ significantly from the ensemble median. Non-significant bins ($p > 0.01$; Methods) are hatched and occur mainly near zero magnitude anomalies or along the figure edges where sample sizes are small due to the rarity of temperature extremes. The significance hatching in Figure 3 is determined as follows: for each magnitude–duration bin we compute the per-run “year of net-zero”, defined as the first year an individual run’s annual emissions reaches net-zero emissions. We then test whether the distribution of net zero years in that bin differs from the distribution across the full ensemble using a Mann–Whitney U test, also known as a two-sided Wilcoxon rank-sum test (Mann & Whitney, 1947; Wilcoxon, 1945). Runs that do not reach net zero by 2100 are excluded.

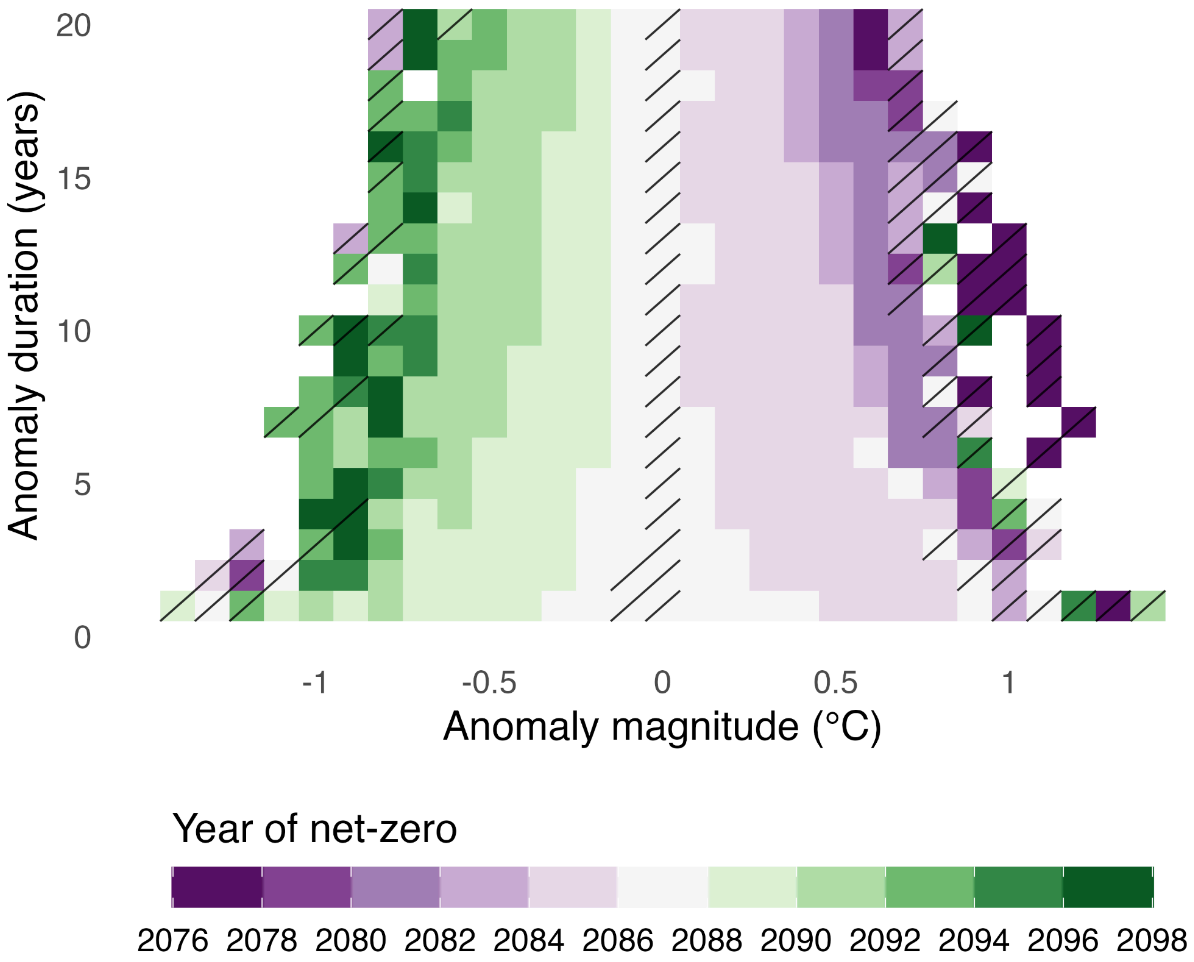

Figure 3: The year of achievement of net-zero emissions depends on the severity and duration of temperature anomalies.

A heatmap of the median year of net-zero carbon emissions as a function of the average magnitude and duration of natural temperature variability across the Monte Carlo ensemble (see Methods). The color scale is centered on 2087, the year when the median emissions trajectory for all runs first reaches net-zero emissions. Hatching marks bins where the difference from the ensemble median is not statistically significant ($p > 0.01$, Mann–Whitney U test).

So far, our analysis has treated variability in terms of global mean temperature. In reality, individuals do not experience the global mean, rather they feel local temperature variability which is not uniform across regions. Tropical regions exhibit relatively little year-to-year fluctuation, whereas the mid-latitudes and poles experience larger swings. To capture a broader range of signals, we replace the temperature anomaly generator in Moore et al. (2022) with draws of temperature anomalies from a high-resolution Earth system model, capturing climate variability from around the world, which we then propagate through a new Monte Carlo ensemble (see Methods 2.3.2).

To assess how long term variability influences mitigation outcomes, we bin simulations by the standard deviation of their temperature anomalies over the full run and plot the corresponding median emissions trajectories (Figure 4). Median trajectories demonstrate that persistently elevated emissions and slower approaches to net zero are associated with higher temperature variability, whereas faster mitigation pathways are associated with lower variability. In the model, larger temperature variability amplifies swings around the warming trend and increases the frequency of cool deviations that, when filtered through the shifting baselines and motivated reasoning components of the model, dampen support for policy (the cognition and opinion components), which in turn slows policy-driven deployment and learning-by-doing in the mitigation system, thus maintaining the status quo. In contrast, smoother climates with fewer cool excursions sustain stronger support and more rapid emissions reductions. Notably, a substantial share of runs in the higher-variability bins do not achieve net zero by 2100, underscoring that variability can prevent decarbonization within the century.

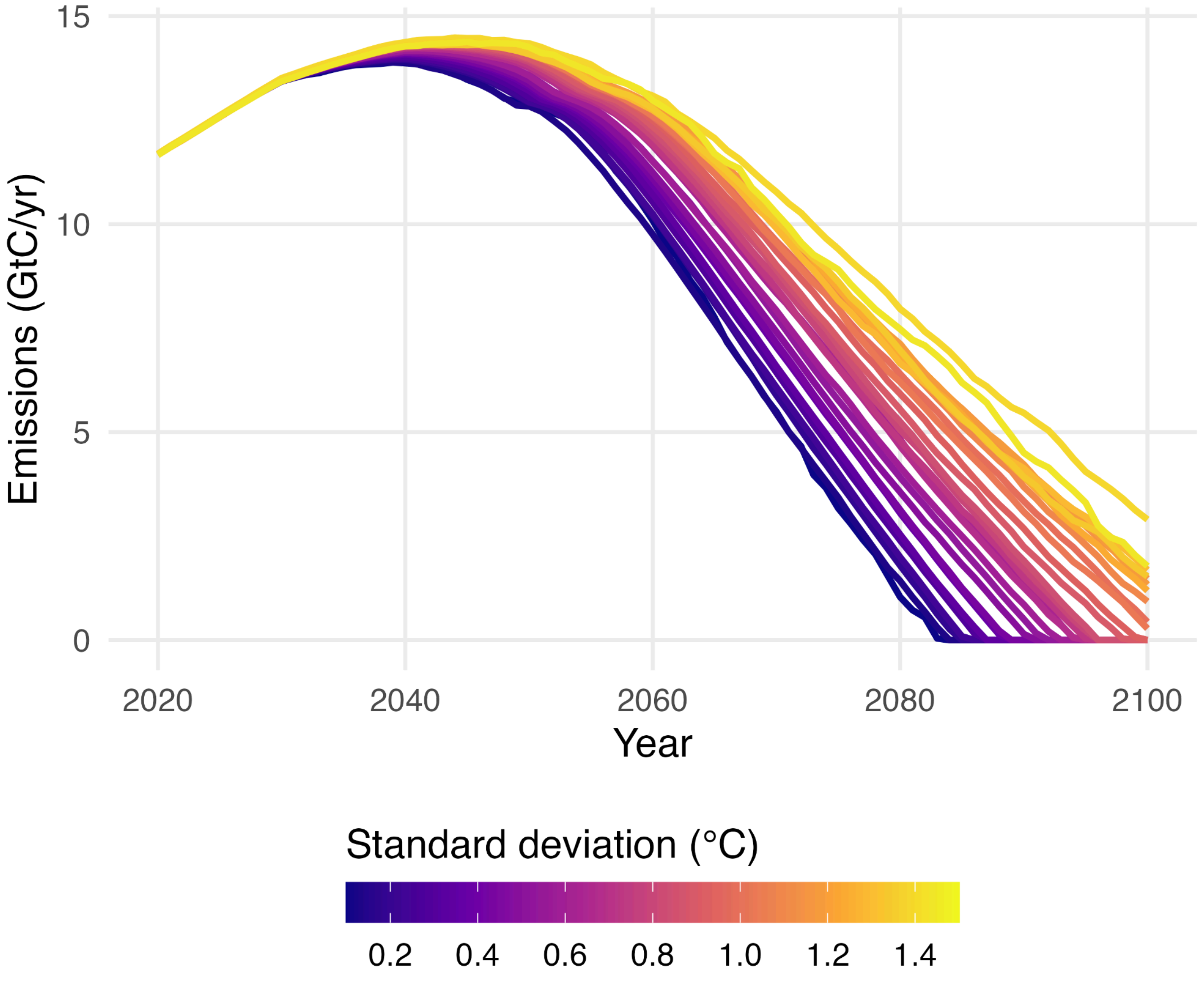

Figure 4: Large temperature variability can mask warming due to climate change, delaying climate mitigation action.

Median emissions trajectories (GtC yr^{-1}) for Monte Carlo runs binned by the standard deviation (°C) of each run's full natural temperature variability time series. Each line shows the median emissions across runs within each bin; the color indicates the bin center. The natural variability of the underlying Monte Carlo ensemble comes from land-based, gridpoint 2-meter temperature anomalies sampled from a high-resolution pre-industrial control simulation of an Earth system model.

Volcanic eruptions represent some of the most powerful perturbations to the climate system, producing sharp and temporary global cooling through the injection of reflective aerosols into the stratosphere which decrease the amount of sunlight reaching the Earth's surface. For example, the 1815 eruption of Mount Tambora produced the "Year Without a Summer," inducing widespread crop failures, food shortages, and social disruption across Europe, Asia, and North America (Oppenheimer, 2003; Raible et al., 2016). Motivated by these historical records, we test how externally forced cooling events might propagate through this coupled climate–social system, shaping public opinion, policy momentum, and ultimately emissions trajectories. We conduct a Monte Carlo ensemble driven by temperature anomalies sampled from the CESM Last Millennium simulations (Otto-Bliesner et al., 2016), which include representations of volcanic eruptions of varying magnitudes. We focus in particular on cooling anomalies attributed to the Tambora eruption, which we impose in the model year 2030 (see Methods), to assess its influence on mitigation dynamics.

The eruption produces a sharp decline in support for climate policy, with public backing requiring roughly five years to recover to pre-eruption levels (Figure 5a). Additional eruptions in the ensemble, occurring in model years 2023, 2046, and 2098 (Supplementary Figure 2), generate similar cooling responses and associated dips in support. Although support recovers as the cooling anomalies subside, the median emissions remain elevated relative to non-volcanic experiments, and the achievement of net-zero is delayed by nearly a decade. These findings suggest that externally forced cooling events can generate a temporary loss of mitigation momentum in the cognition–opinion–policy pathway, leaving lasting imprints on long-term emissions outcomes.

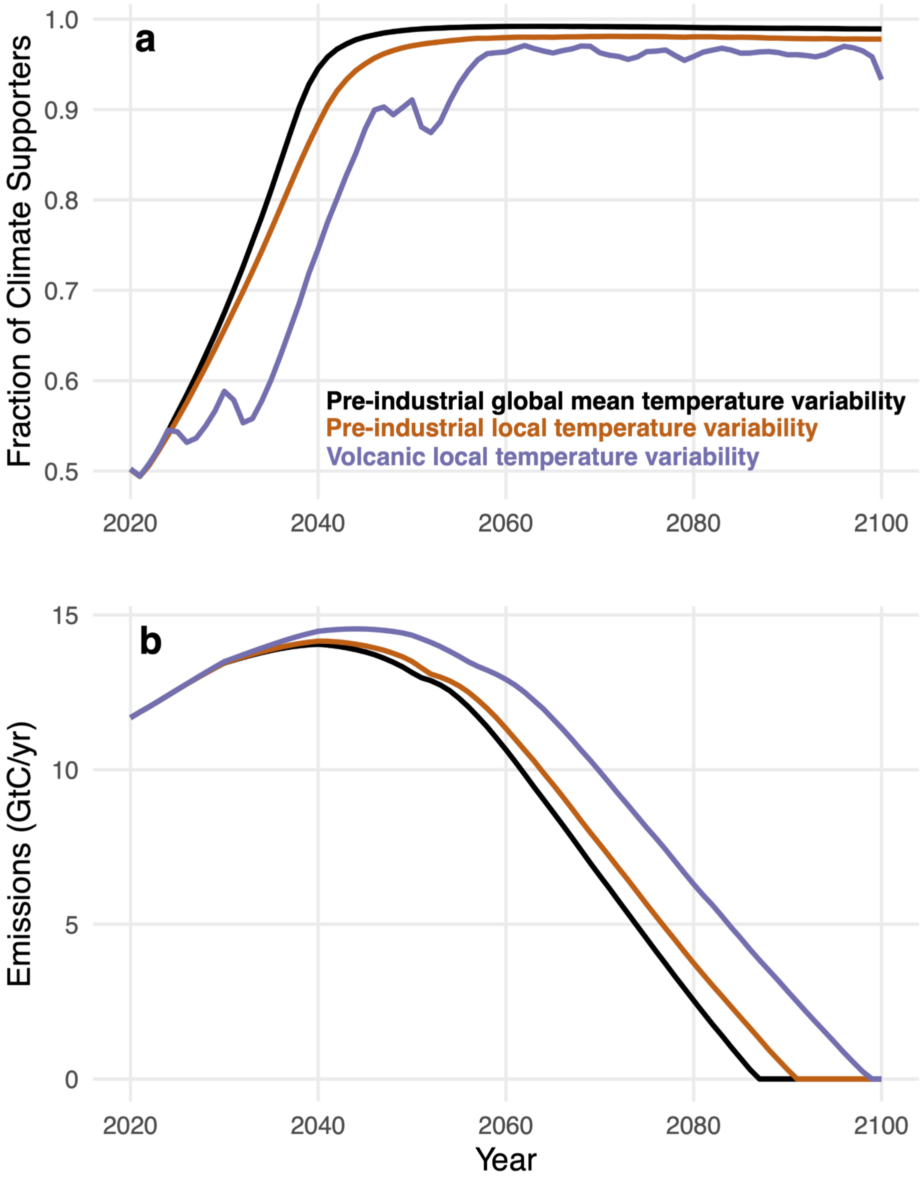

Figure 5: External cooling due to volcanoes causes sharp opinion drops and long-lived emissions delays.

Two-panel comparison of median trajectories from three Monte Carlo ensembles of (top) median fraction of the population supporting climate policy and (bottom) median annual carbon emissions (GtC yr^{-1}). Lines show medians across runs for each dataset: pre-industrial global mean temperature variability (black), pre-industrial local temperature variability (orange), and volcanic local temperature variability (purple).

4. Discussion

These conclusions extend earlier work by Ricke and Caldeira (2014), who used an illustrative model to argue that local climate variability could delay the “time-to-action” for nations by decades. Their model emphasized how people living in a stochastic world may hesitate to implement climate mitigation measures until local weather conditions cross thresholds. Our analysis confirms this insight but advances it in two important ways.

First, we examine these dynamics within a more fully coupled climate–social framework that explicitly represents interactions among public opinion, political institutions, and technological change (Moore et al., 2022). In this framework, climate signals influence public perception, which alters support for climate policy and in turn affects policy enactment and technology deployment. These interactions occur through temporally lagged feedbacks that introduce inertia and nonlinear dynamics into the system. As a result, natural temperature anomalies can propagate through multiple modules of the model and generate deviations in emissions trajectories years down the road.

Second, rather than focusing on time-to-policy thresholds, our results evaluate how climate variability alters the trajectory and timing of mitigation itself, including the achievement of net-zero emissions. This metric directly connects social–climate feedbacks to long-term climate outcomes and enables comparison with emissions pathways produced by integrated assessment models. In this sense, temperature variability acts not just as a delay to policy adoption, but as a driver of mitigation pathways themselves. Reinforcing feedbacks and path dependencies in the model can amplify delays in policy adoption, leading to even larger cumulative effects in global emissions in this coupled system.

We emphasize that our findings should not be interpreted as predictions of specific emissions pathways. The Monte Carlo ensembles employed here are designed to probe underlying mechanisms and sensitivities, not to forecast the timing of policy change or net-zero achievement. Accordingly, while this stylized model does not represent the suite of climate impacts that could influence human opinion, such as floods, ecosystem collapse, and wildfires, many of these indicators are connected to changes in global mean temperature which is represented in the model. The stylized nature of the model means it omits many complexities of real-world politics, economics, and adaptive capacities of communities. Thus, the effects we identify are illustrative rather than predictive. Still, the consistent patterns across ensembles reveal important insights: temporary cool periods tend to dampen momentum, while temporary warm periods accelerate it.

An important feature of our results is the asymmetric influence on emissions pathways between runs forced with high- and low-temperature variability. Simulations with muted variability, which are characteristic of tropical regions, achieve net-zero sooner while those with larger swings, typical of midlatitude climates, are delayed. This juxtaposition highlights a geographic discrepancy: regions with the least temperature variability, often in the Global South, are among the most vulnerable to climate impacts and contribute the least to global emissions (Ngcamu, 2023; Hickel, 2020). Conversely, geopolitically powerful, high-emitting nations at higher latitudes experience greater masking of the warming signal due to larger swings in temperature (Hickel, 2020; Deser et al., 2012), which in our model sustains opposition to climate policy and slows mitigation. This paradigm underscores how the global distribution of temperature variability intersects with the inequitable representation within climate governance, echoing concerns that those most exposed to clear climate signals are least empowered in global decision-making (Diffenbaugh & Burke, 2019).

Our volcanic experiments underscore the role externally forced events may play. Even though the direct cooling from eruptions subsides within a few years, the coupled opinion–policy–technology system produces a lasting legacy: emissions remain higher for decades and net-zero is delayed by nearly ten years. This suggests that temporary disruptions, whether natural or externally forced, can have disproportionately long-lived consequences for mitigation trajectories. While the scenarios are hypothetical, they clarify how abrupt shocks can intersect with social and institutional dynamics to slow decarbonization.

5. Conclusion

Our results demonstrate that natural climate variability can modulate the trajectory of global emissions in a coupled climate–social model. Periods of anomalous warmth accelerate the timing of net-zero by strengthening public support for mitigation, while anomalous cool periods delay it by reducing momentum. These effects are dependent on the character of the temperature variability, being influenced by the magnitude and persistence of anomalies, as well as by their timing and frequency of occurrence. Temperature anomalies due to externally forced cooling events, such as volcanic eruptions, reduce societal motivation to cut emissions, leaving lasting effects on modeled emissions pathways. Together, these findings highlight that natural fluctuations in the climate system can cascade through public perception, political processes, and technology adoption to alter the pace of global decarbonization by years to decades.

These findings point to the value of insulating climate policy from the noise of natural variability. Communication strategies and governance institutions that emphasize long-term trajectories rather than short-term fluctuations are critical to maintaining steady progress. The key lesson is not that net zero will be reached earlier or later by a fixed number of years, but that variability introduces uncertainty into the emissions pathway itself.

Acknowledgments

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Code Availability

Code to reproduce the analysis in this article is provided in an online repository: https://doi.org/10.5281/zenodo.17716309.

Conflict of Interest Statement

The authors declare no conflicts of interest.

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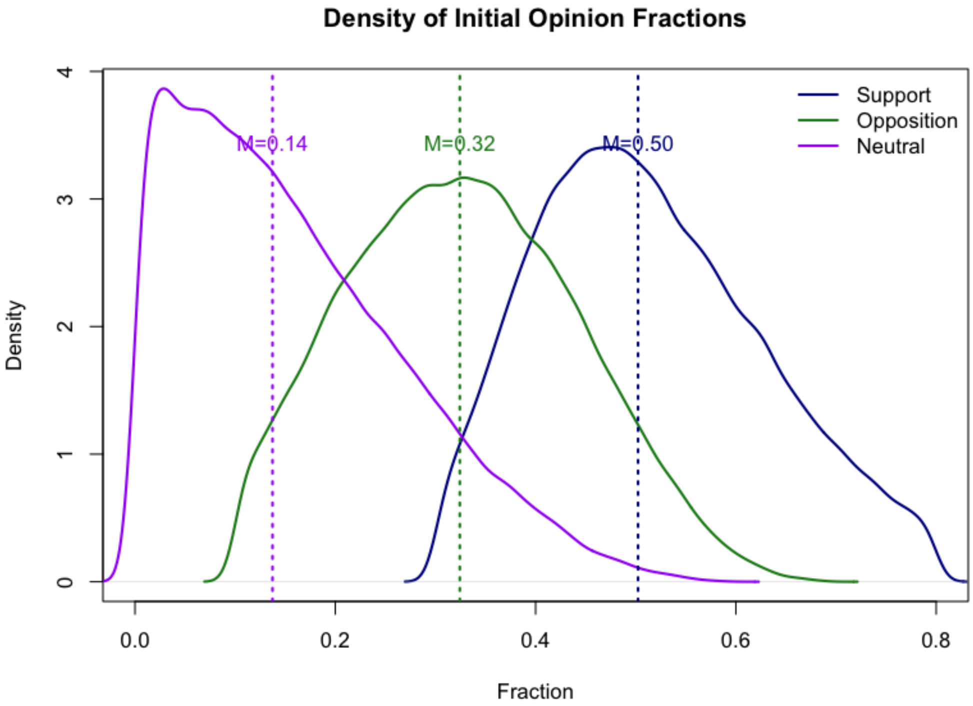
Supplemental Figures and Tables

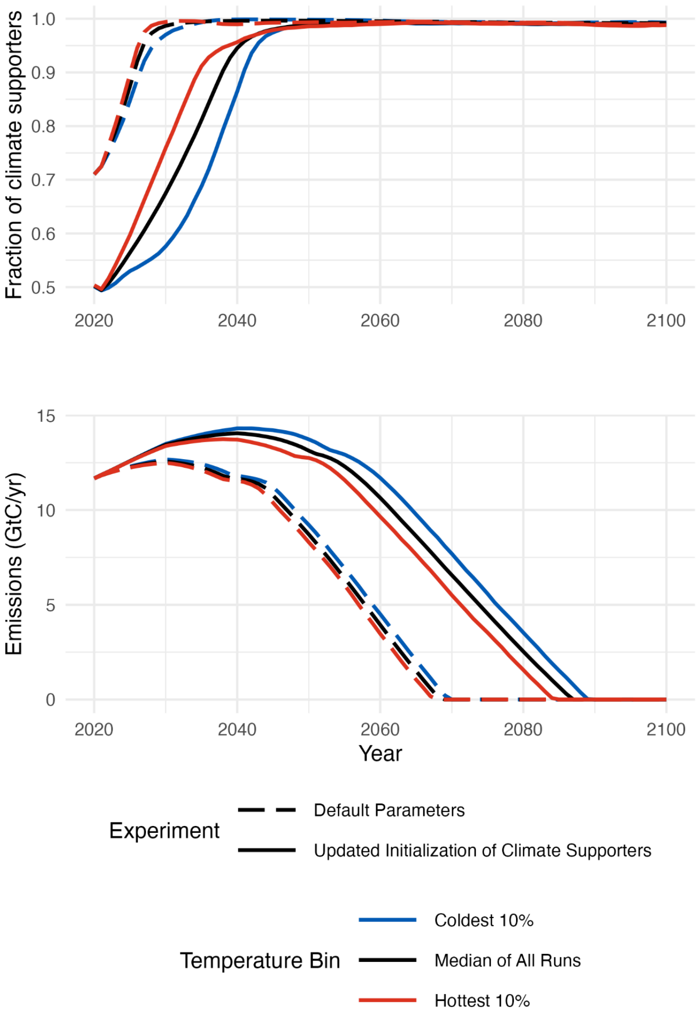
Experiment Name	Variability Source	Spatial Representation	Key Purpose	Figure Reference

Default scheme - global variability	Spectrally generated anomalies calibrated to CESM control	Global mean	Baseline variability experiment; isolate magnitude and duration effects	Fig. 2, Fig. 3
Pre-industrial local temperature variability	CESM pre-industrial control 2m temperature anomalies	Land gridpoints	Assess impact of realistic spatial variability amplitude	Fig. 4, Fig. 5 (orange)
Volcanic local temperature variability	CESM Last Millennium anomalies with Tambora eruption centered in 2030	Land gridpoints	Assess impact of abrupt externally forced cooling	Fig. 5 (purple)

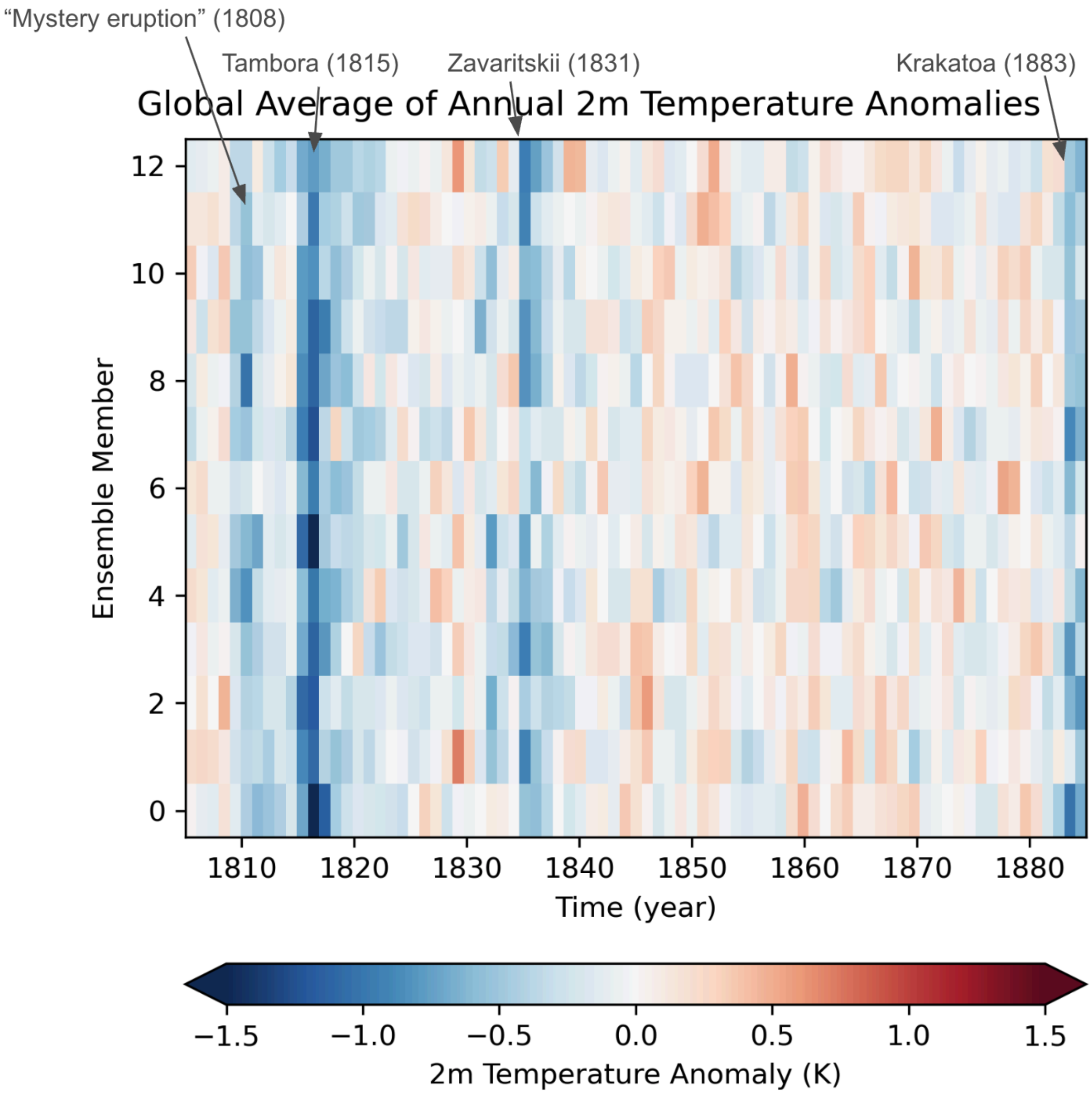
Supplemental Table 1: Summary of Monte Carlo experiments conducted in this study. The table lists each experiment, the source of prescribed temperature variability, its spatial representation, the primary analytical objective, and the associated main-text figures. Experiments include (i) a baseline global spectral variability case calibrated to CESM control simulations, (ii) local variability drawn from CESM pre-industrial control land grid points to represent realistic spatial heterogeneity, and (iii) local variability from the CESM Last Millennium ensemble.



Supplemental Figure 1: Distribution of initial population beliefs used in the Monte Carlo ensemble. Histograms show the distribution of the initial fraction of the population in each opinion group across all 500,000 model runs for the default Monte Carlo ensemble: climate policy supporters (blue), opponents (green), and neutral individuals (purple). Initial conditions are sampled for each run from prescribed probability distributions, producing ensembles centered near 50% supporters, 32% opponents, and 14% neutral. The plotted distributions therefore reflect the realized initial opinion composition across the full Monte Carlo ensemble.



Supplemental Figure 2: Median time series of climate support and emissions across different initializations of fraction of climate supporters. Top panel shows the median fraction of the population supporting climate policy and bottom panel shows median annual carbon emissions in GtC yr^{-1}, plotted for the coldest 10 percent of runs (blue), the median of all runs (black), and the hottest 10 percent of runs (red). Two experiments are compared with different line types: Default parameters shown with long dashed lines Updated initialization of climate supporters shown with solid lines. Natural-variability bins are defined over 2025 to 2034 and medians are taken across runs within each bin for years 2020 to 2100.



Supplemental Figure 3: Cooling anomalies due to volcanic eruptions are visible in the global mean across ensemble members. Area-weighted global annual 2 m temperature anomalies from the CESM Last Millennium 13-member ensemble. Four volcanic eruptions occur in the time series of interest and are labeled accordingly.